IIR System Identification Using Particle Swarm Optimization with Constriction Factor and Inertia Weight Approach

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Abstract— **In this paper a modified version of swarm intelligence technique called Particle Swarm Optimization with Constriction Factor and Inertia Weight Approach (PSO-CFIWA) is applied to IIR adaptive system design problem. The proposed technique PSO-CFIWA in close similarity with Real coded Genetic Algorithm (RGA) and Particle Swarm Optimization (PSO) performs a structured randomized search of an unknown parameter within a multidimensional search space by manipulating a swarm of particles to converge to an optimal solution. PSO being a population based stochastic search method tries to maintain a proper balance between global and local search for achieving the optimum result. The exploration and exploitation of entire search space can be handled efficiently with the proposed technique PSO-CFIWA along with the benefits of overcoming the premature convergence and stagnation problems. The simulation results justify the optimization efficacy of the proposed PSO-CFIWA over RGA and PSO.**

Keywords- IIR Adaptive Filter; RGA; PSO; PSO-CFIWA; Evolutionary Optimization Techniques

I. INTRODUCTION

System identification is a challenging and complex optimization problem due to nonlinearity of the system and dynamic nature of the environment. Almost all physical systems are nonlinear and recursive, so it is convenient to model such systems by using nonlinear models [1-2]. Finite impulse response (FIR) and infinite impulse response (IIR) systems are the competent example of nonlinear systems which can be modelled for unknown plant identification. There have been substantial efforts to establish adaptive IIR filter in place of adaptive FIR filter. For adaptive IIR filter, due to recursive nature, present output not only depends on present input but also the previous inputs and outputs, but in case of FIR filter, the present and past inputs are required to calculate the present output. Hence, more design complexity and larger memory space is demanded for adaptive IIR filter optimization problem. But in system identification problem to achieve a particular level of performance, an adaptive IIR filter requires lower order compared to adaptive FIR filter [3]. Due these advantages adaptive IIR filter is considered for modelling an unknown plant.

In adaptive IIR filtering applications, non differentiable and multimodal nature of error surface is a major point of concern. Classical optimization methods such as least mean square technique are gradient based optimization methods and these techniques are incapable to handle such optimization problems due to following inherent deficiencies: i) Requirement of continuous and differentiable cost function, ii) Usually converges to the local optimum solution or revisits the same sub-optimal solution, iii) Incapable to search the large problem space, iv) Requirement of the piecewise linear cost approximation (linear programming), v) Highly sensitive to starting points when the number of solution variables are increased and as a result the solution space is also increased.

With the above shortfalls of classical optimization method, heuristic and meta-heuristic search algorithms have got attention for adaptive filtering optimization problems. Different optimization techniques aptly used are as follows: Genetic Algorithm (GA) is inspired by the Darwin's "Survival of the Fittest" strategy [4]; human searching nature is mimicked in seeker optimization algorithm (SOA) [5]; the cat swarm optimization (CSO) is based upon the behaviour of cat's tracing and seeking of an object [6]; bee colony algorithm (BCA) is based upon honey searching behaviour of the bee swarm [7-8]; gravitational search algorithm (GSA) is motivated by the gravitational laws and laws of motion [9]; food searching behaviour is mimicked in bacterial foraging algorithm [10] and swarm intelligence is utilized for the development of particle swarm optimization techniques [1], [11-17].

The approach detailed in this paper takes advantage of the power of the stochastic global optimization technique called particle swarm optimization. Particle Swarm Optimization (PSO) is an evolutionary algorithm developed by Eberhart *et al.* [18-19]. Several attempts have been made towards the nonlinear system identification optimization problem [1], [11-17] using PSO algorithm. The PSO is simple to implement and its convergence may be controlled via few parameters. The limitations of the conventional PSO are that it may be influenced by premature convergence and stagnation problem [20-21]. In order to overcome these problems, the PSO algorithm has been modified in this paper and is employed for adaptive IIR filter optimization problem.

This paper describes an alternative technique for handling nonlinear system identification problem using Particle Swarm Optimization with Constriction Factor and Inertia Weight Approach (PSO-CFIWA). Performance of the applied algorithm PSO-CFIWA is analysed with four benchmarked IIR plants. Simulation results are compared with RGA and PSO to demonstrate the effectiveness and better performance of the proposed IIR filter identification method.

The paper is organized as follows: In section II, mathematical expression of an adaptive IIR filter and objective function are formulated. Section III briefly discusses on the heuristic approach PSOCFIWA adopted for adaptive IIR filter design problem. Section IV describes the simulation results obtained by employing RGA, PSO, and PSO-CFIWA. Finally, section V concludes the paper.

II. DESIGN FORMULATION

The main task of the system identification is to vary the parameters of the adaptive IIR filter using evolutionary algorithms unless and until it is matched to the output response of unknown system. In other way, it can be said that in the system identification configuration, the adaptive algorithm searches for the adaptive filter coefficients such that its input/output relationship matches closely to that of the unknown system. Basic block diagram for system identification using adaptive IIR filter is shown below in Fig. 1.

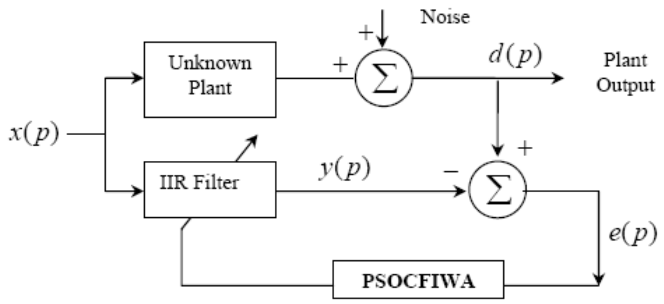

Fig. 1. Adaptive IIR filter for system identification.

This section discusses the design strategy of adaptive IIR filter. The input output relation is governed by the following difference equation [3]:

$$y(p) + \sum_{k=1}^{n} a_k y(p-k) = \sum_{k=0}^{m} b_k x(p-k)$$

where $x(p)$ and $y(p)$ are the filter's input and output, respectively and $n(\geq m)$ is the filter's order. With the assumption of coefficient $a_0 = 0$, the transfer function of the adaptive IIR filter is expressed as given in (1).

$$H(z) = \frac{\sum_{k=0}^{m} b_k z^{-k}}{1 + \sum_{k=1}^{n} a_k z^{-k}} \quad (1)$$

In this design approach the unknown plant of transfer function $H_s(z)$ is to be identified with the adaptive IIR filter $H_{af}(z)$ in such a way so that the output from both the systems matches closely.

In this transfer function filter order is n and $n \geq m$. In this nonlinear system identification problem mean square error (MSE) $J(\omega)$ is considered as the cost function. The optimization problem is defined as the minimization of the value of error signal $e(p)$ in the cost function $J(\omega)$ expressed as in (2):

$$J(\omega) = E[e^2(p)] \approx \frac{1}{N_s} \sum_{p=1}^{N} e^2(p) \quad (2)$$

where $d(p)$ is the desired response, $y(p)$ is the response of the adaptive IIR filter and the error signal is $e(p) = d(p) - y(p)$. N_s is the number of samples. The main objective of the evolutionary algorithm is to minimize the value of the cost function $J(\omega)$ with proper adjustment of coefficient vector ω so that output responses of filter and plant match closely and hence error is minimized.

Here $\omega = [a_0 a_1 ... a_n b_0 b_1 ... b_m]^T$.

III. EVOLUTIONARY ALGORITHM EMPLOYED

A. Particle Swarm Optimization with Constriction Factor and Inertia Weight Approach (PSO-CFIWA)

Evolutionary algorithms stand upon the platform of heuristic optimization methods, which are characterized as stochastic, adaptive and learning in order to produce intelligent optimization schemes. Such schemes have the potential to adapt to their ever changing dynamic environment through the previously acquired knowledge.

Evolutionary techniques RGA and PSO are used for make a comparative study of the results obtained with proposed algorithm Particle Swarm Optimization with Constriction Factor and Inertia Weight Approach (PSO-CFIWA). The discussions on real coded genetic algorithms (RGA) and particle swarm optimization (PSO) methods are available in [22-23]. PSO is a robust population-based stochastic search optimization technique with implicit parallelism, which can easily handle with non-differential cost functions, unlike traditional optimization methods. PSO is less susceptible to getting trapped on local optima unlike GA, Simulated Annealing, etc. Apart from the inherent advantages of PSO the proposed algorithm PSO-CFIWA is also enriched with better searching capacity in a multidimensional search space. For enhancement of global search criteria the basic velocity expression of conventional PSO as in (3) [18-19] is modified in accordance with (4).

$$V_i^{(k+1)} = w * V_i^{(k)} + C_1 * rand_1 * \left(pbest_i^{(k)} - S_i^{(k)}\right) + C_2 * rand_2 * \left(gbest^{(k)} - S_i^{(k)}\right) \quad (3)$$

where $V_i^{(k)}$ is the velocity of i^{th} particle at k^{th} iteration; w is the weighting function; C_1 and C_2 are the positive weighting

factors; $rand_1$ and $rand_2$ are the random numbers between 0 and 1; $S_i^{(k)}$ is the current position of i^{th} particle vector at k^{th} iteration; $pbest_i^{(k)}$ is the personal best of i^{th} particle vector at k^{th} iteration; $gbest^{(k)}$ is the group best of the group at k^{th} iteration. The modified velocity expression of PSOCFIWA is expressed as given in (4).

$$V_i^{k+1} = CFa \times \begin{pmatrix} w^{k+1} * V_i^k + C_1 * rand_1 * \left(pbest_i - S_i^k\right) \\ + C_2 * rand_2 * \left(gbest - S_i^k\right) \end{pmatrix} \quad (4)$$

Normally, C_1 = C_2 = 1.5-2.05 and Constriction Factor (CFa) is given in (5).

$$CFa = \frac{2}{\left|2-\varphi-\sqrt{\varphi^2-4\varphi}\right|} \quad (5)$$

where, φ = C_1 + C_2 , and φ >4. For C_1 = C_2 =2.05, the computed value of CFa = 0.73. The best values of C_1, C_2, and CFa are found to vary with the designs of different filter types.

Inertia weight $\left(w^{k+1}\right)$ at (k+1)th cycle is as given in (6).

$$w^{k+1} = w_{\max} - \frac{w_{\max} - w_{\min}}{k_{\max}} \times (k+1) \quad (6)$$

where $w_{\max}$ =1.0; $w_{\min}$ =0.4; $k_{\max}$ = Maximum number of iteration cycles. The searching point in the solution space is the same as that of conventional PSO and is given in (7).

$$S_i^{(k+1)} = S_i^{(k)} + V_i^{(k+1)} \quad (7)$$

IV. SIMULATION RESULTS AND DISCUSSIONS

Extensive MATLAB simulation studies have been performed for the performance comparison of three algorithms namely, RGA, PSO and PSO-CFIWA for nonlinear system identification optimization problem. The values of the control parameters of RGA, PSO and PSO-CFIWA are given in Table I. All optimization programs are run in MATLAB 7.5 version on core (TM) 2 duo processor, 3.00 GHz with 2 GB RAM.

The simulation studies have been carried out on two different benchmarked examples and for both the examples, two different cases are studied, one with the same order filter and another with reduced order filter. For each case, independent 5 runs are performed using the three algorithms for checking consistency of the results obtained.

A. Example 1

In this example, a second order IIR plant is considered from [5,12,13,15,16] with the transfer function shown as in (8).

$$H_s(z) = \frac{1.25z^{-1} - 0.25z^{-2}}{1 - 0.3z^{-1} + 0.4z^{-2}} \quad (8)$$

TABLE I. CONTROL PARAMETERS OF RGA, PSO AND PSO-CFIWA

Parameters	RGA	PSO	PSO-CFIWA
Population size	120	25	25
Iteration Cycle	400	400	400
Crossover rate	1	-	-
Crossover	Two Point Crossover	-	-
Mutation rate	0.01	-	-
Mutation	Gaussian Mutation	-	-
Selection	Roulette	-	-
Selection Probability	1/3	-	-
C_1	-	2.05	2.05
C_2	-	2.05	2.05
$v_i^{\min}$	-	0.01	0.01
$v_i^{\max}$	-	1.0	1.0
$w_{\max}$	-		1.0
$w_{\min}$	-		0.4
CFa			0.73

1) Case 1

This second order plant $H_s(z)$ can be modelled using second order IIR filter $H_{af}(z)$. Hence the transfer function of the model is assumed by

$$H_{af}(z) = \frac{a_1 z^{-1} - a_2 z^{-2}}{1 - b_1 z^{-1} + b_2 z^{-2}} \quad (9)$$

In (9), a_1, a_2, b_1, and b_2 are the numerator and denominator coefficients, respectively. Tables II-III show the qualitative analysis of results obtained over 5 independent runs for three optimization techniques, namely, RGA, PSO, PSOCFIWA, respectively. Results so obtained in the form of optimized filter coefficients and MSE provide a platform of judgment to identify the best optimization technique. It is observed that the MSE values obtained by the proposed technique PSO-CFIWA are the least as compared to others. It is also noticed from Tables II-III that the optimized coefficients obtained with PSO-CFIWA is more accurate in approximating the coefficients of the unknown plant.

The convergence characteristics for the three models, using RGA, PSO and PSO-CFIWA, as shown in Fig. 2 provide a qualitative measure of the performance of the three algorithms. From Fig. 2, it can be observed that the proposed optimization technique PSO-CFIWA has not only converged to the minimum MSE level but also minimum iteration cycles is required for this achievement. It is also observed that the number of iteration cycles 181, 132 and 85 are required to settle almost minimum level of MSE for the RGA, PSO and PSO-CFIWA algorithms, respectively. Hence it can be argued that the PSO-CFIWA is the fastest among others.

2) Case 2

In this case a higher order plant is modelled by a reduced order filter. For the situation under consideration a second order plant as in (8) is modelled by a first order IIR filter presented in (10).

$$H_{af}(z) = \frac{a_1}{1 + b_1 z^{-1}} \quad (10)$$

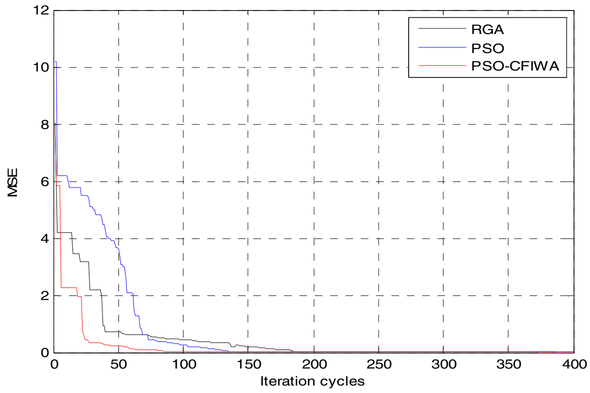

Fig. 2. Convergence characteristic for example-1 modelled using 2nd order IIR filter.

In (10), a_1 and b_1 represents the numerator and denominator coefficients of the first order adaptive IIR filter, respectively. Table IV shows the optimized filter coefficients and MSE values obtained by RGA, PSO and PSO-CFIWA, respectively, when 5 independent runs have been performed for each of the algorithm. Under the close observation of the Table IV, it can be suggested that the results of parameter identification obtained by PSO-CFIWA are more accurate in terms of MSE values, when a second order unknown plant is modelled by a first IIR order filter.

The convergence characteristic for the three models, using RGA, PSO and PSO-CFIWA, shown in Fig. 3 provides a qualitative measure of the performance of the three algorithms. From Fig. 3, it can be observed that the proposed optimization technique PSO-CFIWA has converged to the minimum MSE level with the least number of iteration cycles. It is also observed that the number of iteration cycles 58, 46 and 60 are required to settle almost minimum level of MSE for the RGA, PSO and PSO-CFIWA algorithms, respectively. Hence it can be argued that all the algorithms are fast enough to model the plant with reduced order model.

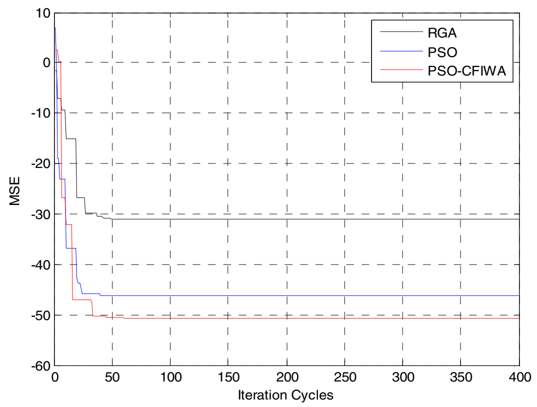

Fig. 3. Convergence characteristic for example-1 modelled using 1st order IIR filter.

B. Example 2

In this example, a third order IIR unknown plant $H_s(z)$ is considered from [13] with the transfer function shown as in (11).

$$H_s(z) = \frac{1}{\left(1-0.5z^{-1}\right)^3} \tag{11}$$

1) Case 1

In this case a third order IIR filter $H_{af}(z)$ is considered for modelling the unknown plant $H_s(z)$. The third order transfer function model of IIR filter is given in (12).

$$H_{af}(z) = \frac{1}{\left(1+a_1z^{-1}+a_2z^{-2}+a_3z^{-3}\right)} \tag{12}$$

In (12), a_1, a_2 and a_3 are the denominator coefficients which are optimized for matching the output response of the unknown plant. Tables V-VI show the optimized filter coefficients and MSE values obtained by RGA, PSO and PSO-CFIWA, respectively, for the same order IIR filter used for modelling the unknown plant. From the above mentioned Tables V-VI it is noticed that PSO-CFIWA not only attains the lowest MSE values in different runs but also the least deviation is observed for any coefficient under consideration.

The convergence characteristics for the above mentioned optimization models, RGA, PSO and PSO-CFIWA as shown in Fig. 4 provides a qualitative measure of the performance of the three algorithms. From Fig. 4, it is observed that the PSO-CFIWA has not only converged to the minimum MSE level but also the minimum iteration cycles are required for this achievement. It is also observed that the number of iteration cycles of 87, 81 and 76 are required to settle to the minimum level of MSE for the RGA, PSO and PSO-CFIWA algorithms, respectively. Hence it can be inferred that the PSO-CFIWA is the fastest among others.

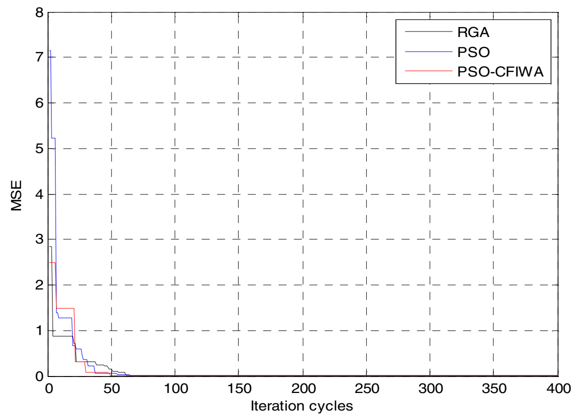

Fig. 4. Convergence characteristic for example-2 modelled using 3rd order IIR filter.

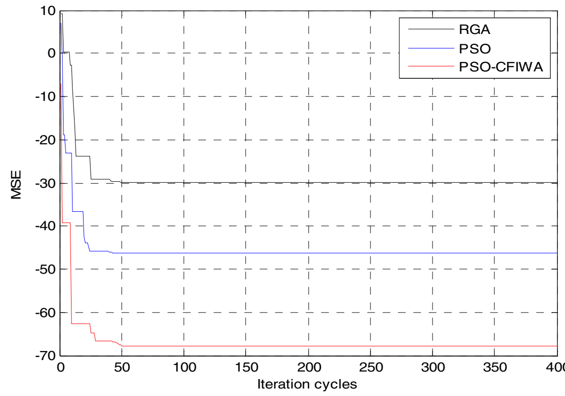

Fig. 5. Convergence characteristic for example-2 modelled using 2nd order IIR filter.

2) Case 2

In this case a higher order plant is modelled by a reduced order filter. For the situation under consideration a third order plant as in (11) is modelled by a second order IIR filter as presented in (13).

$$H_{af}(z) = \frac{1}{\left(1 + a_1 z^{-1} + a_2 z^{-2}\right)} \quad (13)$$

In (13), a_1 and a_2 are the denominator coefficients which are optimized for modelling the third order unknown plant. Table VII shows the optimized IIR filter coefficients and MSE values obtained by using RGA, PSO, and PSO-CFIWA, respectively, when five independent runs have been performed for each of the algorithm. Under the close observation of the Table VII, it is observed that the results obtained by PSO-CFIWA are more accurate in terms of MSE values, when an unknown plant of third order is modelled by a second order IIR filter. The convergence profile for the three models, using RGA, PSO and PSO-CFIWA, as shown in Fig. 5 provides a qualitative measure of the performance of the RGA, PSO, and PSOCFIWA algorithms, respectively. The proposed optimization technique PSO-CFIWA has converged to the minimum MSE level and is evident from Fig. 5. It is to be noted that the number of iteration cycles 45, 40 and 52 are required to settle to the minimum level of MSE for the RGA, PSO and PSO-CFIWA algorithms, respectively. Hence it can be justified that the PSO-CFIWA based model mimicked the unknown plant closely with considerably lower value of MSE.

TABLE II. OPTIMIZED COEFFICIENTS AND MSE OBTAINED BY USING RGA AND PSO

Runs	RGA					PSO				
	a_1	a_2	b_1	b_2	MSE	a_1	a_2	b_1	b_2	MSE
Run 1	1.2498	-0.2521	-0.3014	0.4001	2.3706e-04	1.2500	-0.2500	-0.3000	0.4000	4.0850e-09
Run 2	1.2498	-0.2506	-0.3002	0.3996	1.3730e-04	1.2500	-0.2500	-0.3000	0.4000	4.0471e-010
Run 3	1.2502	-0.2504	-0.3001	0.3999	2.0080e-05	1.2500	-0.2500	-0.3000	0.4000	4.3061e-09
Run 4	1.2501	-0.2501	-0.3004	0.4002	1.2400e-04	1.2500	-0.2500	-0.3000	0.4000	2.6194e-10
Run 5	1.2506	-0.2501	-0.3004	0.3998	2.0541e-04	1.2500	-0.2500	-0.3000	0.4000	1.0104e-10

TABLE III. OPTIMIZED COEFFICIENTS AND MSE OBTAINED BY USING PSO-CFIWA

Runs	PSO-CFIWA				
	a_1	a_2	b_1	b_2	MSE
Run 1	1.2500	-0.2500	-0.3000	0.4000	2.0205e-15
Run 2	1.2500	-0.2500	-0.3000	0.4000	3.9548e-16
Run 3	1.2500	-0.2500	-0.3000	0.4000	2.0155e-14
Run 4	1.2500	-0.2500	-0.3000	0.4000	3.4697e-15
Run 5	1.2500	-0.2500	-0.3000	0.4000	4.0916e-16

TABLE IV. OPTIMIZED COEFFICIENTS AND MSE VALUES OBTAINED BY USING RGA, PSO AND PSO-CFIWA

Runs	RGA			PSO			PSO-CFIWA		
	a_1	b_1	MSE	a_1	b_1	MSE	a_1	b_1	MSE
Run1	0.3996	-0.6518	1.4465	0.4223	-0.6267	1.4295	0.4865	-0.6022	0.6531
Run2	0.5379	-0.6049	1.5373	0.4293	-0.6283	1.1749	-0.4178	0.6362	0.7375
Run3	0.4833	-0.6330	1.7401	0.4192	-0.6387	1.1434	0.4252	-0.6205	0.5250
Run4	0.4587	-0.6547	1.7113	0.4250	-0.6504	1.2172	-0.3975	0.6328	0.6876
Run5	0.4821	-0.6327	1.5206	0.4258	-0.6481	1.4564	-0.4635	0.6029	0.5590

TABLE V. OPTIMIZED COEFFICIENTS AND MSE VALUES OBTAINED BY USING RGA AND PSO

Runs	RGA				PSO			
	a_1	a_2	a_3	MSE	a_1	a_2	a_3	MSE
Run1	-1.5070	0.7577	-0.1252	9.5496e-004	-1.4999	0.7498	-0.1249	5.6131e-008
Run2	-1.4875	0.7241	-0.1106	6.9538e-004	-1.5000	0.7501	-0.1250	6.4369e-009
Run3	-1.5009	0.7518	-0.1259	3.1273e-006	-1.5000	0.7499	-0.1249	3.9403e-008
Run4	-1.5009	0.7518	-0.1256	5.0537e-005	-1.5000	0.7501	-0.1250	7.9844e-009
Run5	-1.5002	0.7507	-0.1255	1.4660e-006	-1.5000	0.7500	-0.1250	1.1334e-009

TABLE VI. OPTIMIZED COEFFICIENTS AND MSE VALUES OBTAINED BY USING PSO-CFIWA.

Runs	PSO-CFIWA			
	a_1	a_2	a_3	MSE
Run1	-1.5000	0.7500	-0.1250	1.9593e-015
Run2	-1.5000	0.7500	-0.1250	1.2372e-015
Run3	-1.5000	0.7500	-0.1250	1.9180e-016
Run4	-1.5000	0.7500	-0.1250	1.2680e-016
Run5	-1.5000	0.7500	-0.1250	1.1378e-015

TABLE VII. OPTIMIZED COEFFICIENTS AND MSE VALUES OBTAINED BY USING RGA, PSO AND PSO-CFIWA

Runs	RGA			PSO			PSO-CFIWA		
	a_1	a_2	MSE	a_1	a_2	MSE	a_1	a_2	MSE
Run1	-1.38303	0.517163	0.045844	-1.38116	0.51428	0.02864	-1.38200	0.51519	0.010233
Run2	-1.38170	0.51257	0.050735	-1.3819	0.51343	0.021846	-1.38388	0.51488	0.011560
Run3	-1.38453	0.51584	0.04495	-1.38377	0.51346	0.0203966	-1.38199	0.515189	0.010911
Run4	-1.38388	0.51488	0.04624	-1.3814	0.51485	0.02463	-1.38550	0.51705	0.010928
Run5	-1.3855	0.51705	0.04371	-1.38303	0.51716	0.02292	-1.38289	0.51246	0.00924

V. CONCLUSIONS

This paper presents an accurate approach for designing the adaptive IIR filters using a modified PSO called particle swarm optimization with constriction factor and inertia weight (PSOCFIWA). Extensive simulation study with benchmarked IIR plants justify that the proposed optimization technique PSO-CFIWA is a viable plant identification optimization tool for modelling the nonlinear system. It is also evident from the simulation results that PSO-CFIWA outperforms RGA and conventional PSO in terms of optimization of filter coefficients, acquisition of the lowest MSE values and fast convergence to the optimal solution. Addition of constriction factor and modification of inertia weight in each iteration cycle of the traditional PSO helps to find optimal solution in the multidimensional search space without the problem of premature convergence and entrapment to sub optimal solution. By comparative studies, it is shown that the PSO-CFIWA is more accurate for parameter identification, in both the cases of either modelling an unknown system with the same order filter or the reduced order filter.

REFERENCES

[1] G. Panda, D. Mohanty, B. Majhi and G. Sahoo, "Identification of nonlinear systems using particle swarm optimization technique," IEEE Congress on Evolutionary Computation, pp. 3253-3257, 2007.

[2] D. J. Krusienski and W. K. Jenkins, "Design and performance of adaptive systems based on structured stochastic optimization strategies," IEEE Circuits and Systems Magazine, vol. 5, no. 1, pp. 8-20, 2005.

[3] Z. M. Hussain, A. Z. Sadik and P. O'Shea, "Digital Signal Processing-An Introduction with MATLAB Applications," Springer-Verlag, 2011.

[4] Q. Ma, and C. F. N. Cowan, "Genetic algorithms applied to the adaptation of IIR filters," Signal Processing, vol. 48, pp. 155-163, 1996.

[5] C. Dai, W. Chen and Y. Zhu, "Seeker optimization algorithm for digital IIR filter design," IEEE Trans on Industrial Electronics, vol. 57, no. 5, May 2010.

[6] G. Panda, P. M. Pradhan and B. Majhi, "IIR system identification using cat swarm optimization," Expert Systems with Applications, (Elsevier), vol. 38, no. 10, pp. 12671-12683, 2011.

[7] N. Karaboga and M. H. Cetinkaya, "A novel and efficient algorithm for adaptive filtering: artificial bee colony algorithm," Turk. J. Elec. Eng and Comp Sci, vol. 19, no. 1, pp. 175-190, 2011.

[8] N. Karaboga, "A new design method based on artificial bee colony algorithm for digital IIR filters," Journal of the Franklin Institute, (Elsevier), vol. 346, pp. 328-348, 2009.

[9] E. Rashedi, H. Nezamabadi, S. Saryazdi, "Filter modelling using gravitational search algorithm," Engineering Applications of Artificial Intelligence, (Elsevier), vol. 24, pp. 117-122, 2011.

[10] B. Majhi and G. Panda, "Bacterial foraging based identification of nonlinear dynamic system," IEEE Congress on Evolutionary Computation, CEC 2007, Singapore, pp.1636-1641.

[11] S. Chen and B. L. Luk, "Digital IIR filter design using particle swarm optimization," Int. J. Modelling, Identification and Control, vol. 9, no. 4, pp. 327-335, 2010.

[12] B. Luitel and G. K. Venayagamoorthy, "Particle swarm optimization with quantum infusion for system identification," Engineering Applications of Artificial Intelligence, vol. 23, pp. 635-649, 2010.

[13] X. Yu, J. Liu and H. Li, "An adaptive inertia weight particle swarm optimization algorithm for IIR digital filter," IEEE Int. Conf. on Artificial and Computational Intelligence, pp. 114-118, 2009.

[14] W. Fang, J. Sun and W. Xu, "A new mutated quantum behaved particle swarm optimizer for digital IIR filter design," EURASIP Journal on Advances in Signal Processing, vol.2009, article ID. 367465, pp. 1-7.

[15] D. J. Krusienski and W. K. Jenkins, "Adaptive filtering via particle swarm optimization," in Proc. 37th Asilomar Conf. on Signals, Systems and Computers, vol.1, pp. 571-575, Nov. 2003.

[16] D. J. Krusienski and W. K. Jenkins, "Particle swarm optimization for adaptive IIR filter structure," IEEE Congress on Evolutionary Computation, CEC 2004, vol. 1, pp. 965-970.

[17] W. Fang, J. Sun and W. Xu, "Analysis of adaptive IIR filter design based on quantum behaved particle swarm optimization," in Proc. IEEE 6th World Congress on Intelligent Control and automation, China, pp. 3396-3400, 2006.

[18] J. Kennedy and R. Eberhart, "Particle swarm optimization," in Proc. IEEE Int. Conf. on Neural Network, vol. 4, pp. 1942-1948, 1995.

[19] R. Eberhart and Y. Shi, "Comparison between genetic algorithm and particle swarm optimization," in Evolutionary Programming VII, pp. 611-616, Springer, 1998.

[20] S. H. Ling, H. H. C. Iu, F. H. F. Leung, and K. Y. Chan, "Improved hybrid particle swarm optimized wavelet neural network for modeling the development of fluid dispensing for electronic packaging," IEEE Trans. on Industrial Electronics, vol. 55, no. 9, pp. 3447–3460. 2008.

[21] B. Biswal, P. K. Dash, and B. K. Panigrahi, "Power quality disturbance classification using fuzzy C-means algorithm and adaptive particle swarm optimization," IEEE Trans. on Ind. Electron., 2009, vol. 56, no. 1, pp. 212–220.

[22] S. Mandal, S. P. Ghoshal, R. Kar, D. Mandal, "Optimal Linear Phase FIR Band Pass Filter Design using Craziness Based Particle Swarm Optimization Algorithm" Journal of Shanghai Jiaotong University (Science), Springer, Vol. 16, No. 6, pp. 696-703, 2011.

[23] S. Mandal, S. P. Ghoshal, R. Kar, D. Mandal, "Design of Optimal Linear Phase FIR High Pass Filter using Craziness based Particle Swarm Optimization Technique" Journal of King Saud University – Computer and Information Sciences, Elsevier, vol. 24, pp. 83–92, 2012.